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Malik, Husnain and Rakotonirainy, Andry and Maire, Frederic D. (2010)  
*Comprehensive evaluation of driver gaze pattern using fuzzy rules for driver training*. In: Proceedings of 20th Canadian Multidisciplinary Road Safety Conference, 6-9 June 2010, Hilton Niagara Falls, Ontario.

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# Comprehensive Evaluation of Driver Gaze Pattern Using Fuzzy Rules for Driver Training

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## Abstract

The over representation of novice drivers in crashes is alarming. Research indicates that one in five drivers' crashes within their first year of driving. Driver training is one of the interventions aimed at decreasing the number of crashes that involve young drivers. Currently, there is a need to develop comprehensive driver evaluation system that benefits from the advances in Driver Assistance Systems. Since driving is dependent on fuzzy inputs from the driver (i.e. approximate distance calculation from the other vehicles, approximate assumption of the other vehicle speed), it is necessary that the evaluation system is based on criteria and rules that handles uncertain and fuzzy characteristics of the drive.

This paper presents a system that evaluates the data stream acquired from multiple in-vehicle sensors (acquired from Driver Vehicle Environment-DVE) using fuzzy rules and classifies the driving manoeuvres (i.e. overtake, lane change and turn) as low risk or high risk. The fuzzy rules use parameters such as *following distance*, *frequency of mirror checks*, *gaze depth and scan area*, *distance with respect to lanes* and *excessive acceleration or braking* during the manoeuvre to assess risk. The fuzzy rules to estimate risk are designed after analysing the selected driving manoeuvres performed by driver trainers. This paper focuses mainly on the difference in gaze pattern for experienced and novice drivers during the selected manoeuvres. Using this system, trainers of novice drivers would be able to empirically evaluate and give feedback to the novice drivers regarding their driving behaviour.

## Résumé

La surreprésentation des conducteurs débutants dans les accidents de la route est alarmante. Des recherches ont montré qu'un conducteur sur cinq est impliqué dans un accident lors de sa première année de conduite. Une des solutions pour réduire ce nombre d'accidents des jeunes conducteurs est la formation à la conduite. Actuellement, il y a un besoin de développer un système complet d'évaluation des conducteurs s'appuyant sur les systèmes d'aide à la conduite (Advanced Driver Assistance Systems ADAS). Conduire dépend de la recherche d'informations dans l'environnement de conduite, informations dont l'évaluation est incertaine ou approximative (par exemple pour l'évaluation de la distance à d'autres véhicules et la vitesse de ces véhicules). Dès lors il est nécessaire qu'un tel système d'évaluation soit basé sur des critères et règles qui intègrent l'incertitude de la conduite.

Cet article présente un tel système capable d'évaluer le risque (faible à fort) de différentes manœuvres (dépassement de véhicule, changement de voie et intersection). Cette évaluation analyse le flot de données obtenu par de multiples détecteurs places dans un véhicule (enregistrant des données sur le conducteur, le véhicule et l'environnement) grâce à l'utilisation de la logique floue. Des règles sont créées en utilisant des paramètres tels la distance au véhicule qui précède, la fréquence de l'utilisation des rétroviseurs, la distance à laquelle regarde le conducteur ainsi que l'aire scannée, la vitesse latérale (par rapport au marquage au sol) et les accélérations et décélérations abruptes. Ces règles permettent de déterminer le risque de la manœuvre. Ces règles sont définies grâce à l'analyse de manœuvres réalisées par des moniteurs de conduite. Cet article se concentre sur l'analyse des différences de regards entre les conducteurs expérimentés et les conducteurs débutants. L'utilisation du système développé devrait permettre aux moniteurs de conduite d'évaluer empiriquement les conducteurs apprentis et ainsi les aider à conseiller les conducteurs débutants afin d'améliorer leur conduite.

## INTRODUCTION

Road crashes are the single highest killer of 15-24 year-olds in industrial countries [1]. Driving is a complex task which requires the driver to assess subjectively their position with respect to the lanes and surrounding vehicles and anticipate the future trajectory of their vehicle within that scenario. Therefore driving safely takes time to learn and needs extensive practice. With time, the actions of driving i.e. changing gears, looking in the rear-view mirror, steering, correctly assessing situations, reacting appropriately, etc. becomes a naturalistic behaviour and efficient. However, the novice driver has to think about these actions, increasing overall mental workload and possibly distracting attention from the road [2]. It has been demonstrated that a major contributing factor to crashes of newly licensed driver, is the failure to scan effectively for potential risks [3-6]. We hypothesize that the failure to understand what is really important for inexperienced driver to learn, in terms of risky driving, is one of the many reasons restraining us to build better training programs.

[ Relatively little research has focused on the different errors that drivers make, or about the causal factors that contribute to these errors made by drivers [19]. In-order to comprehensively tackle driving issues, a complete and integrated framework needs to be developed that should include and examine all the parameters that influence driving (i.e. cues related to road, vehicle and driver). Our approach consist of assessing the level of risk (Low, Medium, High) during manoeuvres, based on the parameters acquired from the Driver, Vehicle and Environment (DVE). Once the assessment has been made, an effective feedback system needs to be put in place that can help driver trainers to better explain the driving drawbacks of novice trainee drivers.

This paper describes the use of fuzzy set theory for risk evaluation and analysis of the manoeuvres. The safety judgment models are made up with the help of fuzzy logic. Fuzzy logic is an efficient tool for processing rule-based human knowledge and experience, by which an algorithm can be constructed through linguistic rules [7]. At core of a fuzzy logic based system is an inference system, which mimics human perception and decision making process. This inference system is responsible for deriving results from inputs using fuzzy rules. In a system that analyses driver behaviour, the input variables can include information related to following gap, the relative speed between the host and other vehicles. The output variable is the safety (i.e. high or low risk) for carrying out a manoeuvre.

This main objective of this paper is to identify comprehensively the difference in gaze pattern for experienced and novice drivers during the selected manoeuvres. The comparison is formally based on the use of fuzzy inference system

## 1. RELATED RESEARCH

The value and effectiveness of driver training as a mean of improving driver behaviour and road safety continues to fuel research and societal debates. Knowledge about what are the subjective and objective characteristics of safe and unsafe driving is extensive [9-11]. Some research literature suggests that changes in traditional pre-license training programs could influence basic car control and road law knowledge skill but would not have significant impact on crash reductions or traffic violations [9].

Apart from the development of basic vehicle-handling skills, some researchers believe that current training methods have not generally been found to contribute to increase in road safety [9, 13]. For example: gaze pattern have been found out to play an important role in hazard perception. But researchers [14] points out that by just training driver gaze pattern and hence enabling them to recognise risk would not reduce the willingness of young drivers to engage in unsafe driving. Even though these researchers do concur that fixating appropriately during a driving task does not guarantee that the driver will take appropriate action if the risk actually appears. However, not fixating appropriately during the driving task that requires urgent attention virtually guarantees that things will get worse [14]. Therefore driver training's impact on road safety cannot be completely ruled out.

Furthermore, parents also have an important role in increasing the amount of supervised driving the novice drivers undertake, which seems to reduce subsequent risky behaviour. One of the key aspects of driver training programs is assessment or feedback on the driving performance. This can be either self-assessment or assessment from another group or individual. Extensive research has revealed that it is not so much the lack of basic driving skills that caused the crash, but higher order skills. These higher order skills deal with risk perception, situational awareness, risk acceptance, self-assessment [15].

It is not possible for instructors and driving mentors to simultaneously assess accurately the drivers' actions, cognitive skill, and vehicle control relative to environmental circumstances. However Advanced Driving Assistance Systems (ADAS) acting as the in-vehicle devices can add a significant set of useful functionalities to existing driver training programs. Such new functionalities offer possibilities to enrich and improve the learner's understanding of the driving task. Along with this, during driving events such as lane changes and lead vehicle breaking events, drivers are sometimes too close to lead-vehicles for some proportion of a trip, even if they are driving safely. What separates the safe from unsafe following? Similarly, for most of the critical driving skills, empirical answers are needed to design a customized driver feedback technology to influence traffic safety. The difficulty of this task is only amplified in the case of more complex driving behaviours, such as changing lanes or making a left hand turn.

A system that can provide an integrated feedback on driver's proficiency is still lacking in current driver training and education. To our knowledge, there is no comprehensive automated feedback system that lets the drivers and driver trainers to

effectively and efficiently observe and measure all the variables relevant to safety involved in driving (i.e. Driver , Vehicle and Environment also known as DVE).

Drivers on roads demonstrate a rich set of behaviours that make driving environment very complex in terms of possible scenarios and outcomes. Fuzzy logic has proven itself as a promising mathematical approach for addressing subjectivity, ambiguity, imprecision and uncertainty of linguistic expressions [16]. The driving task is performed based on estimates after considering input parameters from our senses such as current speed, location of other vehicles and follower vehicles in the same and/or the adjacent lanes, gap in the target lane, distance to the location of target turn. Fuzzy logic is appropriate to be applied in a driving scenario because not all of the above mentioned input parameters are crisp values and cannot be estimated accurately by a driver. In reality, all of these parameters involve some extent of fuzziness. Every decision of a driver (i.e. the intention of the driver to change lanes), as an output parameter is fuzzy and involves human approximations. The rule base (in the form of IF...THEN rules) with fuzzy reasoning closely resembles human knowledge and behaviour as they use linguistic terms and are capable of handling complex situations using certain rules [16].

This paper would detail the differences in gaze between experienced and novice drivers during overtake manoeuvres. It would further design fuzzy rules for driver gaze risk assessment.

## 2. Risk Assessment Based on Fuzzy Logic

This section deals with creating a low risk driving model based on fuzzy set theory. The driver thinking and reaction process is continuous over time and modifies itself to the environmental constraints. All of the driver inputs while driving are not based on crisp values, rather they have some uncertainty based on subjective perception (i.e. distance from the turn, distance from the object in front, the position of a certain vehicle in future.).

At the empirical level, uncertainty is an inseparable companion of almost any measurement, resulting from a combination of inevitable measurement errors and resolution limits of measuring instruments [16]. Fuzzy logic has been proven to deal with these uncertainties [16]. Fuzzy logic is based on a three step process that is fuzzification, inference and then defuzzification.

The fuzzification process is based on the membership functions. The role of the fuzzy membership functions is to represent subjective human perception using the concept of a fuzzy set [7]. In a classical set or crisp set, the objects in a set are called elements or members of the set. A characteristic function or membership function  $\mu_A(x)$  is defined for any element (x) in the universe U having a crisp value of 1 or 0. For every  $x \in U$ ,

$$\mu_A(x) = \begin{cases} 1 & \text{for } x \in A, \\ 0 & \text{for } x \notin A. \end{cases} \quad (1)$$

For the classical set or crisp set, membership functions take a value of 1 or 0, for fuzzy sets, the membership function can take values in the interval [0, 1]. The range between 0 and 1 is referred to as the degree of membership [8]. A fuzzy set can have several membership functions  $\mu_A$  defined as functions from the well defined universe U, into a unit interval, 0-1.

$$\mu_A : U \rightarrow [0,1] \quad (2)$$

Where  $\mu_A$  is a membership function belonging to the interval [0, 1]. This membership function can represent the degree of the subjective notions of a vague class with an infinite set of values between 0 and 1 [7].

The inference part of the fuzzy logic is performed using fuzzy rules. A fuzzy rule has two components: an if-part (also referred to as the antecedent) and a then-part (also referred to as the consequent):

IF {antecedent}, THEN{consequent}

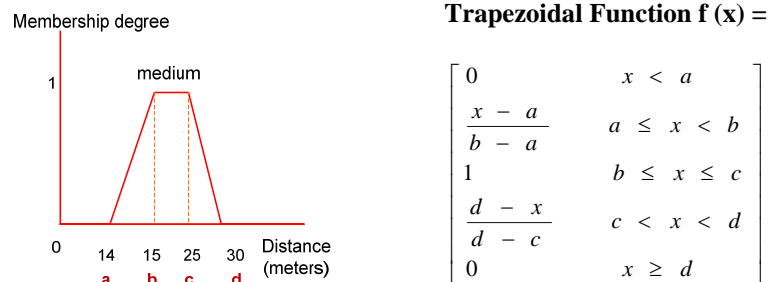
The antecedent describes a condition, and the consequent describes the conclusion that can be drawn when the condition holds. For instance, Table 2 presents the inference rules between the two sets, which are:

The number of *gaze points in 1st and 2nd segment* of the road ahead (1st set).  
And  
number of *gaze points in 3rd segment* of the road ahead (2nd set)

Figure 3-a,b shows the trapezoidal fuzzy membership functions for 1<sup>st</sup> set and 2<sup>nd</sup> set which are Low (L), Medium (M) and High (H). One of the rules in Table 2 for 'High' number of fixations in 1<sup>st</sup>, 2<sup>nd</sup> segment and 'Low' number of fixations in 3<sup>rd</sup> segment implies 'Medium' risk can be written as:

IF {No. of fixations in 1<sup>st</sup>,2<sup>nd</sup> segment==‘H’ AND No. of fixations in 3<sup>rd</sup> segment ==‘L’}  
THEN { Risk is Medium }

Function to compute the degree of membership for an input ‘x’ using a trapezoidal function for four parameters {a,b,c,d} is shown below in Figure 1. This rule based system introduces a quantifiable degree of uncertainty into the modelling process in-order to accommodate the natural or subjective perception of real variables [8]. It models the human decision making process using fuzzy membership functions and fuzzy rules (i.e. if/then rules). These rules are deduced from human expertise (i.e. driver trainer). In-order to construct these rules, multiple negotiations of the same manoeuvre were reviewed.



**Figure 1: A trapezoidal membership function and equation to compute degree of membership for a given value ‘x’.**

## 2.1 Methodology

A set of sensors (i.e. cameras for eye tracking, GPS, Laser scanner) were used for the experiment. These sensors were fitted in a test vehicle and the data from these sensors were time stamped and synchronized.

The test car (host car) was a 2007 automatic Toyota 4WD. Two video cameras of FaceLab [17], which were facing the driver, recorded the head and eye movements. While another camera mounted with a fisheye lens recorded the scene ahead of the test vehicle. The other sensors recorded data related to following distance, frequency of mirror checks, gaze depth and scan area, distance with respect to lanes and excessive acceleration or braking.

### 2.1.1 Participants

Both experienced and novice drivers were recruited randomly for this experiment (three participants for each group). The experienced drivers were also driver trainers. The average number of driving years for novice and experienced driver was 1.8 and 30 years respectively.

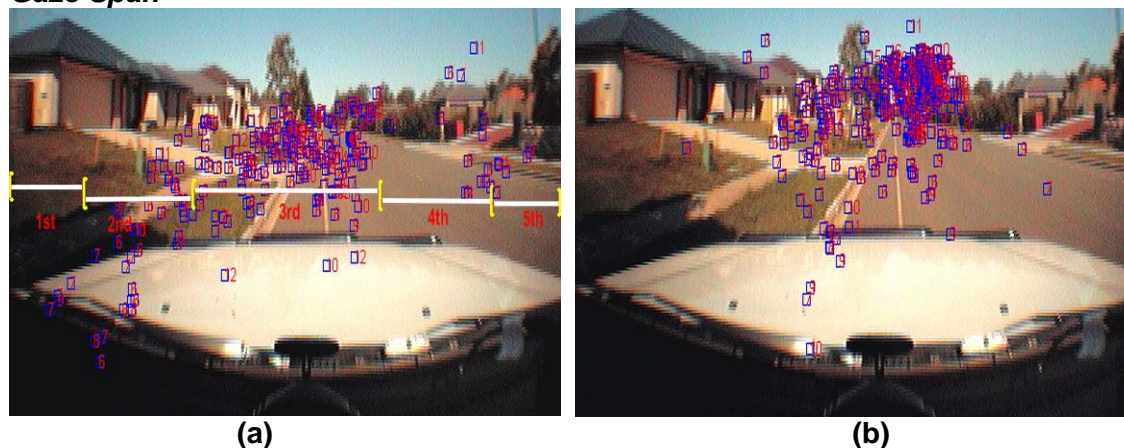
### 2.1.2 Experimental Drive

The drivers' eye/head movement along with vehicle dynamics and lane/obstacle positioning were recorded using sensors while driving on a closed circuit track. Each lap consisted of two overtake and two turn scenario. After getting familiar with the track, each participant was required to complete ten laps (with overtakes and turns), to measure consistency of driver behaviour. The maximum speed limit for the host vehicle on this track was 60km/h. The vehicle to be overtaken had a maximum speed limit of 20km/h. These were the only vehicles present on the track thus creating controlled parameters for the drive.

### 2.1.3 Results

In-order to effectively monitor driver behaviour, every manoeuvre is divided into three parts namely: pre-manoeuve, manoeuvre and post-manoeuve. This helps to objectively assess driver behaviour not just during manoeuvre but even at the approach and end of a particular manoeuvre. The two items identified as significant with respect to gaze evaluation were gaze span and fixation duration.

#### *Gaze Span*



**Figure 2 (a) Displays an experienced driver's gaze pattern during overtake on an image of road ahead. The yellow markers display the segmentation of the road ahead into five segments.**

**(b) Displays a novice driver's gaze pattern during an overtake manoeuvre.**

As mentioned above, the focus of this paper is to assess drivers' gaze pattern while they perform overtake manoeuvres. Figure 2 shows the drivers' fixation points overlaid on an image of the road ahead. The image of the road in front was divided into five symmetrical segments to have a better understanding of the gaze patterns amongst different groups of drivers. These five segments helped to create a histogram of the gaze on the road ahead. It was observed that novice drivers focused solely on the 3rd region (i.e. middle of road ahead), while experienced drivers had a much wider gaze span during overtake. Another observation was that novices were generally more focused than experienced drivers to fixate only on the road far ahead. Such gaze pattern was consistently noticed in each part of the manoeuvre (i.e. Pre overtake, During overtake and Post overtake).

To quantify this difference in gaze patterns between novice and experienced drivers, Generalized Linear Models (GLMs) were used. GLMs from the Poisson family were fitted to obtain the expected number of gaze points knowing the following factors: experience of the driver, part of the manoeuvre and position of the gaze on the region of the road ahead.

The formula below models the relationship between gaze numbers and the different factors mentioned above.

$$\begin{cases} \eta = \sum_i \beta_i \cdot \text{Factor}_i & \rightarrow (a) \\ E(\text{No. of gaze} | \text{Factors}) = \exp(\eta) & \rightarrow (b) \end{cases} \quad (3)$$

where  $\text{Factor}_i$  is either 1 or 0 and  $\beta$  is the estimate for the factors (refer to Table 1). In order to compute the expected number of gaze in a region/segment, (a) returns  $\eta$  (eta) which is a linear combination of the factors that we want to investigate. The link function logarithm is used to model the relationship between the linear predictor (eta) and the expected number of gaze given the factors. This is presented in (b) using the inverse link function (exp).

The impacts of the different factors obtained using GLM for evaluating gaze span are summarized in Table 1 below. All these factors are statistically significant (p-value < 0.05). The level of statistical significance as assessed by p-value is represented by the number of '\*'.

Factors	Estimate ( $\beta$ )	Std. Error	p-value	Code
Intercept ( $\alpha$ )	3.97719	0.0291	< 2e-16	***
Inexperienced	-0.78733	0.04504	< 2e-16	***
OT Manoeuvre	0.67727	0.02202	< 2e-16	***
Post OT Manoeuvre	-0.66212	0.03074	< 2e-16	***
Segment2	-0.23887	0.03526	1.24E-11	***
Segment3	2.09423	0.04752	< 2e-16	***
Segment4	-0.42173	0.07999	1.35E-07	***
Segment5	-0.82046	0.09276	< 2e-16	***
Inexperienced – Segment3	-1.20267	0.05166	< 2e-16	***
Inexperienced – Segment4	-0.79411	0.09381	< 2e-16	***
Inexperienced - Segment5	-0.53378	0.10651	5.40E-07	***
Signif. codes: p-val= 0 '***' p-val < 0.001 '**' p-val < 0.01 '*' p-val < 0.05 '.'				

\*OT – Overtake

**Table 1: Linear regression estimates for factors influencing gaze span**



Table 1 shows that experienced and inexperienced drivers have significant difference in gaze span while performing the overtake manoeuvre. The most gaze difference amongst the two groups was noticed in the 1st, 2nd and 3rd segments of the road image. Novice drivers tend to look a lot less in the 1st and 2nd segment as compared to the experienced drivers. Along with this, novice drivers look more in the 3rd segment as compared to the experienced drivers. Hence showing consistency with the previous research which mentions that horizontal variance in gaze was greater for experienced drivers [18]. This enabled the creation of fuzzy sets and rules to identify gaze patterns risk assessment.

Figure 3 presents the trapezoidal membership functions and their relationship for the number of fixations on the different segments of the road ahead. These membership functions have been created after analysing the difference in gaze patterns between novice and experienced drivers. GLMs estimate of the drivers' gaze and the standard deviation between the gazes for both groups of drivers, assisted in designing the membership functions.

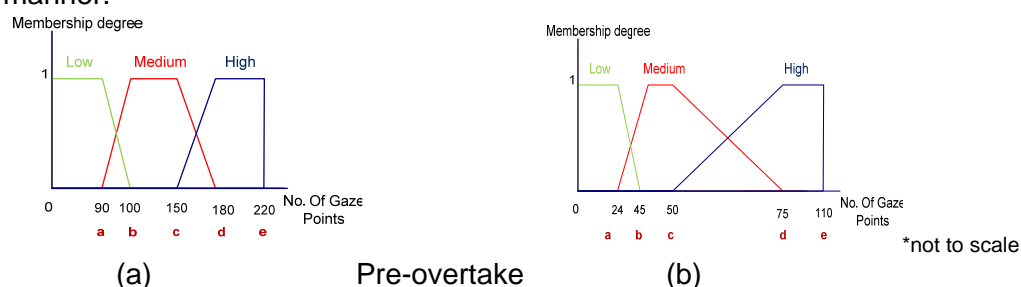
Table 2 along with Figure 3 is utilized to assess the risk for "gaze pattern" task. This assessment is a necessary component to gauge multiple manoeuvres' (i.e. turn, overtake, T-crossing.) risk. In Figure 3, X axis represents the membership functions and their relationship for the fuzzy set, whereas Y axis presents the degree of membership to the functions (i.e. L, M, H). The risk is evaluated on a scale of 0-1, 1 being the highest risk.

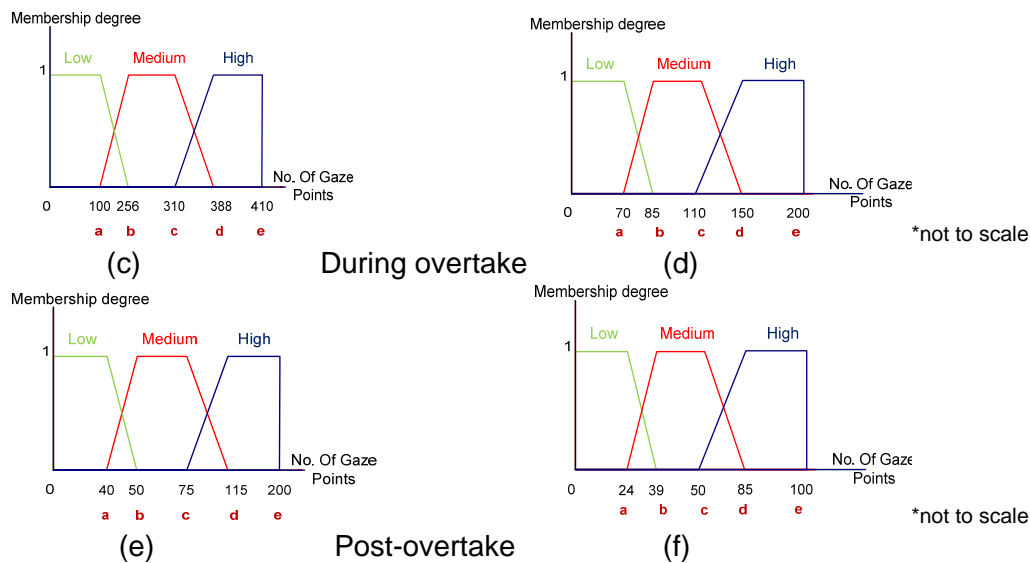
Table 2 presents the fuzzy rules for gaze risk assessment. This risk is calculated by comparing the number of fixations in the 1<sup>st</sup> and 2<sup>nd</sup> segment of the road (shown in Figure 2-b) against the number of fixations in the 3<sup>rd</sup> segment of the road. As mentioned above, novice drivers look less in the 1<sup>st</sup> and 2<sup>nd</sup> segment as compared to experienced drivers during overtake and more in the 3<sup>rd</sup> segment as compared to experienced drivers. Using these fuzzy sets and rules, any eye gaze pattern can be distinguished as high/low risk. This would eventually assist driver trainers in providing an effective and empirical assessment of trainee's scanning behaviour.

No. of fixations in 1 <sup>st</sup> and 2 <sup>nd</sup> segment	No. of fixations in the 3 <sup>rd</sup> segment of the road		
	Low (L)	Medium (M)	High (H)
Low (L)	VeryHigh_Risk	High_Risk	High_Risk
Medium (M)	Medium_Risk	Medium_Risk	Medium_Risk
High (H)	Medium_Risk	Low_Risk	VeryLow_Risk

**Table 2: Inference rules for gaze risk assessment using number of fixations in the 1<sup>st</sup> plus 2<sup>nd</sup> segment and 3<sup>rd</sup> segment**

By utilizing such a system that is able to evaluate gaze risk, will eventually help to flag any parts of manoeuvre that the driver might not have performed in a low risk manner.





**Figure 3: Trapezoidal membership functions for the number of gaze points for:**  
**Pre-overtake in (a) the 3<sup>rd</sup> segment (b) the 1<sup>st</sup> and 2<sup>nd</sup> segment combined**  
**During overtake in (c) the 3<sup>rd</sup> segment (d) the 1<sup>st</sup> and 2<sup>nd</sup> segment combined**  
**Post-overtake in (e) the 3<sup>rd</sup> segment (f) the 1<sup>st</sup> and 2<sup>nd</sup> segment combined**

As mentioned before that along with noticing a significant difference in gaze span of the novice and experienced drivers, the other significant finding was the dissimilarity in the fixation duration of the two groups of drivers. Details are explained below.

### Fixation Duration

Previous researchers [20] showed that drivers fixate on areas of the environment where information could be obtained that would reduce the likelihood of a crash. As already stated above, experienced drivers show more horizontal transitions than novice drivers. Along with this, the other notable difference was observed in the duration of fixation for both categories of drivers (i.e. novice and experienced). Experienced drivers tend to vary their fixation duration a lot more than the novice driver. Novice drivers tend to fixate for the same amount of time on a tight gaze span, whereas experienced drivers vary their fixations more hence adapting with the changing driving conditions.

The impacts of the different factors obtained using GLM for evaluating fixation durations are summarized in Table 3 below. Similar to 'gaze span' evaluation for both categories of drivers, the fixation duration for the different groups (novice and experienced) showed a difference. The fuzzy rules and membership functions to identify risky fixation pattern have been designed similar to 'gaze span'.

Table 3 below identifies inexperience as a significant factor contributing to the inability to vary fixation (p-value < 0.05).

Factors	Estimate ( $\beta$ )	Std. Error	p-value	Code
Intercept ( $\alpha$ )	8.7118	0.4538	< 2e-16	***
Inexperienced	-3.4785	0.6731	< 2e-16	***
Signif. codes: p-val= 0 <sup>(***)</sup>	p-val < 0.001 <sup>(***)</sup>	p-val < 0.01 <sup>(**)</sup>	p-val < 0.05 <sup>(*)</sup>	

**Table 3: Linear regression estimates for factors influencing variation in fixations**

Hence both of these driver behaviours (i.e. gaze span and fixation duration) have been identified as attributes that differentiates experienced from novice drivers. By

empirically evaluating their linguistic expressions for 'low risk' gaze patterns using fuzzy rules, the risks are computed for performing each manoeuvre. This allows the driver trainers to provide an efficient and objective feedback to trainees.

## CONCLUSION

Young drivers have a high crash liability relative to those with a few years of driving experience. This suggests that experience teaches some skills that enable experienced drivers to avoid crashes. By teaching such skills to young drivers through effective driver training would adversely impact young driver crash rates.

Differences in sequences of fixations have been found between novice and experienced drivers. The experiment depicted that novice drivers have a shorter gaze span as compared to their experienced counterparts. In addition, novice drivers' vary their fixation duration a lot less than experienced drivers. Developing a fuzzy model for driver gaze span and fixation duration has clear practical applications both in testing and training of drivers. Such a model would allow driving attributes to be identified that are required for low risk manoeuvring. This paper identifies the differences in gaze patterns for novice and experienced drivers. Based on the findings, fuzzy set theory was utilized for risk evaluation and classification of drivers' gaze during the three stages of manoeuvres (pre-manoeuvre, during manoeuvre and post-manoeuvre). The rules designed will enable driver trainers to assess drivers' gaze pattern as high/low risk. Future work on other complex manoeuvres (u-turn, roundabout) along with monitoring vehicle dynamics and vehicle-environment interaction, will allow a more comprehensive assessment. Feedback on the attempted driving manoeuvres, highlighting both strengths and weaknesses of the driver will act as an effective measure to improve driving skills. Thus, driver training remains an important road safety intervention to improve driving performance and abilities, particularly amongst young people.

## ACKNOWLEDGEMENTS

The authors would like to acknowledge the management team of RoadCraft Driver Training Centre for helping them to conduct the test drives. Authors appreciate the assistance of Graham Smith for providing a driver trainer's perspective on evaluating drivers. Gregoire Larue's input on GLMs and translation is acknowledged.

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